

# Computation of Compressive Strength of GGBS Mixed Concrete using Machine Learning



Swati, Jitendra Khatti, Kamaldeep Singh Grover

**Abstract:** Concrete is a composite material formed by cement, water, and aggregate. Concrete is an important material for any Civil Engineering project. Several concretes are produced as per the functional requirements using waste materials or by-products. Many researchers reported that these waste materials or by-products enhance the concrete properties, but the laboratory procedures for determining the concrete properties are time-consuming. Therefore, numerous researchers used statistical and artificial intelligence methods for predicting concrete properties. In the present research work, the compressive strength of GGBS mixed concrete is computed using AI technologies, namely Regression Analysis (RA), Support Vector Machine (SVM), Decision Tree (DT), and Artificial Neural Networks (ANNs). The cement content (CC), C/F ratio, w/c ratio, GGBS (in Kg & %), admixture, and age (days) are selected as input parameters to construct the RA, SVM, DT, ANNs models for computing the compressive strength of GGBS mixed concrete. The CS\_MLR, Link\_CS\_SVM, 20LF\_CS\_DT, and GDM\_CS\_ANN models are identified as the best architectural AI models based on the performance of AI models. The performance of the best architectural AI models is compared to determine the optimum performance model. The correlation coefficient is computed for input and output variables. The compressive strength of GGBS mixed concrete is highly influenced by age (curing days). Comparing the performance of optimum performance AI models and models available in the literature study shows that the optimum performance AI model outperformed the published models.

**Keywords:** Compressive strength; GGBS, Support Vector Machine, Artificial Neural Networks

## I. INTRODUCTION

Concrete is the dominant construction material used in any Civil Engineering project. It is a mixture of cement, aggregate, and water [19]. Plain cement concrete and reinforced cement concrete are types of concrete. The plain cement concrete performs better in compression, but it fails in tension. The reinforcements are provided to overcome this failure. Several supplementary cementitious materials (SCM) are used to improve the concrete properties.

These cementitious materials can be waste materials or by-products. The limestone, natural pozzolana, silica fume, GGBS, and natural calcined pozzolana are the cementitious materials [4]. The published research works on the use of waste materials in the concrete show that the strength properties of concrete can be improved by adding a suitable quantity of waste material. Still, the determination of strength properties is time – consuming task. The strength properties of concrete are determined at twenty – eight days of curing. The compressive, flexural, and split tensile strength are the strength properties of concrete determined experimentally at 28, 56, 90 days of curing. Numerous researchers applied statistical methods, namely simple, logistic, & multiple regression analysis, and AI methods, namely SVM, GPR, DT, and ANN, etc., to compute the compressive strength of concrete.

By mapping the interrelationship with the water-cement ratio and the relative strength or gel/space ratio, the compressive strength of ordinary concrete can be predicted [15]. The artificial neural network removes the formation of complicated analytical equations. The precision of the neural network is the same while providing neurons in the range of 4 to 8 at the hidden layer [16]. In the early ages, it was assumed that the water-cement ratio played an important role in predicting the compressive strength of concrete. Still, one of the published articles reported that other concrete ingredients also influence the compressive strength of concrete. In the published work, the compressive strength of high-performance concrete was predicted using ANN because of the complexity of materials. The artificial neural network model outperformed the regression model in the published work [25]. The backpropagation neural networks outperformed the multiple regression analysis in predicting the strength and slump of the high-strength concrete and ready mixed concrete [9]. The grade of cement, w/c ratio, water dosages, and cement dosages, the maximum size of coarse aggregate, fine modulus of sand, sand-aggregate ratio, aggregate-cement ratio, slump, admixture affect the prediction of compressive strength of concrete. The neural network makes better predictions of compressive strength as compared to regression analysis [10]. The artificial neural network has the potential to predict the compressive strength of concrete from 0 to 28 days of curing [17]. The genetic expression programming (GEP) outperforms the regression analysis and artificial neural network in predicting the compressive cement strength with the performance of 0.8803 ( $R^2 = 0.775$ ) [2]. The GGBS enhances the strength properties of concrete. The GGBS was mixed at 20%, 40%, 60% and 80% for 0.3, 0.4 and 0.5 w/c ratio concrete.

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# Computation of Compressive Strength of GGBS Mixed Concrete using Machine Learning

The authors computed the compressive strength of GGBS mixed concrete for 3, 7, 28, 90, 360 days of curing and reported that ANN can be an alternative technology for computing the compressive strength [3]. For any construction work, the compressive strength of concrete must be known. The authors predicted the compressive strength of concrete at 28 days using early age results. In this published study, the authors developed a rational polynomial equation and reported that the proposed equation can predict the compressive strength of concrete at 28 days of curing [12]. The fly ash (Class C) improves the compressive strength. The age, water binder ratio, fly ash content, and aggregate binder ratio plays an important role in predicting the compressive strength of concrete at 28 and 90 days of curing. The authors reported that the ANN can predict the compressive strength of concrete [20].

The dismantled concrete was used to improve the compressive strength of concrete. The compressive strength of concrete was predicted for 3, 7, 28, and 91 days of curing. The study was carried out using 1178 datasets of concrete. The ANN models were developed using 17 input parameters. After analyzing the results, it was concluded that the ANN has the potential to predict the compressive strength for 3, 7, 28, and 91 days of curing [8]. The two-coefficient-based rational polynomial equation can also predict the strength parameters of concrete [14]. The regression models were developed using w/c ratio, cementitious content, water content, workability, and curing days to predict the compressive strength of concrete. The authors reported that the proposed regression model predicted the compressive strength of concrete with an accuracy of 95% [5]. The Levenberg-Marquardt algorithm-based ANN model outperforms the genetic programming model in predicting compressive strength [6]. The artificial neural network predicts silica fume and metakaolin mixed concrete's compressive strength more accurately than the MLR model [13]. The compressive strength of concrete was predicted using SVM, random forest, and ANN models. The random forest model outperformed the SVM and ANN model with a performance of 0.9497 [21]. The artificial neural network can predict the compressive strength of green concrete with a performance of 88.45% [22]. The ANN model can predict the compressive strength with high performance and accuracy [18] [24]. The artificial neural network has the potential to predict the compressive strength of cement mortar [1]. From the study of published articles, it has been observed that most of the authors used the artificial neural network AI approach to predict the compressive strength of concrete and results compared with regression, GEP, SVM model. The published research work was carried out using a different number of datasets. It has also been observed that the multiple regression, support vector machine, decision tree, and artificial neural network AI approaches have not been applied for predicting the compressive strength of GGBS mixed concrete. The present study has the following aims.

- Employ regression, support vector machine, decision tree, and artificial neural network models in MATLAB R2020a for predicting compressive strength of GGBS mixed concrete.

- Draw the correlation between input and output parameters of the model to determine the influence of input parameters on the prediction of compressive strength.
- Compare the performance of models to determine the optimum performance model.
- Draw the comparison of the performance of the optimum performance model with published models.

## II.METHODOLOGY

The regression analysis (multiple regression analysis – MLR), support vector machine (SVM), decision tree (DT), and artificial neural network (ANN) models have been used to predict the compressive strength of GGBS mixed concrete. The MLR, SVM, DT, ANN AI approaches have been discussed below with applied hyperparameters.

### 1.1 Regression Analysis

Regression analysis is the most powerful tool of statistics. The regression analysis is used for predicting and forecasting. The simple regression analysis is the fundamental regression analysis that consists of single dependent and independent variables. The multiple regression analysis consists of more than one dependent and independent variable. In the present study, multiple regression analysis has been performed to predict the compressive strength of concrete. An equation has been derived from the training of the multiple regression analysis (CS\_MLR) model.

$$\text{CS\_MLR} = 86544 - 2.176 \cdot \text{CC} - 49759 \cdot \text{C/F ratio} - 146.8 \cdot \text{w/c ratio} + 13.346 \cdot \text{GGBS (Kg)} - 50.69 \cdot \text{GGBS (\%)} - 6.129 \cdot \text{SP} + 0.9228 \cdot \text{Age} \quad (1)$$

Where CC is cement content, GGBS is ground granulated blast-furnace slag in % and Kg, C/F ratio is coarse & fine aggregate ratio, w/c ratio is the water-cement ratio, and SP is superplasticizer. Equation 1 has been used to predict the compressive strength of GGBS mixed concrete for different ages.

### 1.2 Support Vector Machine

The support vector machine (SVM) is based on supervised learning applied to solve the classification and prediction problems [7]. The SVM is inspired by statistical learning frameworks or developed by Vapnik (1995). In the present study, the support vector machine models have been developed using the Regression Learning Tool of MATLAB R2020a. The SVM is based on kernel functions, namely Gaussian, Linear, Quadratic, and Cubic. In the present work, the Gaussian, Linear, Quadratic, and Cubic kernel functions have been used to develop the SVM to predict the compressive strength of GGBS mixed concrete. The hyperparameters of SVM models are given in Table 1.

**Table 1 – Hyperparameters of SVM models**

Hyperparameters	Status	Values
Kernel Functions	Auto	Gaussian, Linear, Quadratic, Cubic
Box Constraint	Auto	Auto Calculated
Kernel Scale	Auto	1
Epsilon	Auto	Auto Calculated
Standardize Data	Enable	Yes
Optimizer	Enable	Bayesian Optimizer
Acquisition Function	Enable	Expected improvement per second plus
Iterations	Default	Default (30)
Max. Training time (sec.)	Default	Default (300)
Number of Grid Divisions	Default	Default (10)

The model architecture of Gaussian, Linear, Quadratic, and Cubic kernel functions-based SVM model is given in Table 2.

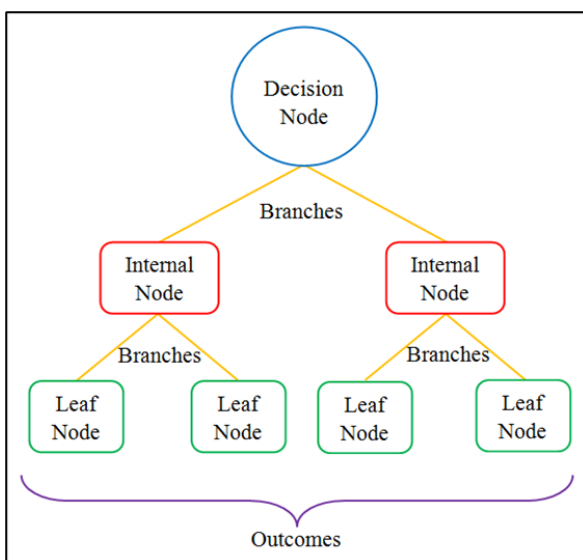
**Table 2 – Architecture of SVM Models**

Kernel Function	Kernel Notation	Model Architecture
Gaussian	GaussK	GaussK_CS_SVM
Linear	LinK	LinK_CS_SVM
Quadratic	QuadK	QuadK_CS_SVM
Cubic	CubicK	CubicK_CS_SVM

The best architectural SVM model for predicting the compressive strength of GGBS mixed concrete is determined based on the performance comparison of SVM models.

### 1.3 Decision Tree

The decision tree is another supervised machine learning technique used to solve classification and regression or forecasting problems. A decision tree consists of nodes (node, root node, inner node, leaf) and branches. The architecture of a simple decision tree with nodes and branches is shown in Figure 1.



**Figure 1. Architecture of simple decision tree**

In this study, the twenty-leaf size decision tree has been employed in MATLAB R2020a to predict the compressive strength of GGBS mixed concrete. The model architecture of twenty leaf size-based DT model is 20LF\_CS\_DT. The hyperparameters of DT models are given in Table 3.

**Table 3 – Hyperparameters of DT model**

Hyperparameters	Status	Values
Minimum Leaf Size	Manual	Twenty
Surrogate Decision Splits	Default	Off
Max. Surrogates per Nodes	Default	10
Optimizer	Enable	Bayesian Optimizer
Acquisition Function	Enable	Expected improvement per second plus
Iterations	Default	Default (30)
Max. Training time (sec.)	Default	Default (300)
Number of Grid Divisions	Default	Default (10)

### 1.4 Artificial Neural Networks

The artificial neural network (ANN) is a network of layers, and these layers are interconnected with neurons. The ANN is based on supervised, unsupervised, and reinforcement learning. The artificial neural network is also used for solving regression and classification problems. The multilayer perceptron class-based ANN model is the most popular neural network. Every neural network model has feedforward and backpropagation processes to solve the issues. In the present study, the multilayer perceptron class-based ANN models have been developed with different backpropagation algorithms. The hyperparameters of ANN models are given in Table 4.

**Table 4 - Hyperparameters of ANN model**

Hyperparameters	Value
Hidden layer(s)	One
Neurons	Ten
Backpropagation algorithm(s)	LM, BFG, SCG, GDM, GD, GDM
Activation function(s)	Sigmoid, Linear function
Train: Validation ratio	80: 20
Epochs	1000
Network type	Feedforward backpropagation
Network class	Multilayer perceptron class
Mu	0.001
Max fail	6
Min gradient	10e-7

## III. DATA ANALYSIS

The present study has been carried out using published datasets of Venu (2014). A total of 56 datasets have been used to develop regression, SVM, DT, and ANN models. The dataset consists of GGBS (in kg & %), cement content, fine aggregate content, coarse aggregate content, superplasticizer (in %), age, and compressive strength. The C/F ratio has been calculated from the coarse and fine aggregate. The cement content (CC), C/F ratio, GGBS (in kg & %), superplasticizer (in %) have been used as input parameters to develop the prediction models.

1.5 Descriptive Statistics

Descriptive statistics is a summary of the datasets used for studying the characteristics of datasets.

The statistics parameters are the minima, maxima, mean, mode, median, standard deviation (StDev), and confidence level (CL) at 95%. The descriptive statistics of datasets are given in Table 5.

Table 5 – Descriptive statistics of datasets of GGBS concrete

Particulars	Cement (Kg)	C/F ratio	W C ratio	GG BS (Kg)	GG BS (%)	SP (%)	Age (Days)	CS (Mpa)
Min	130.80	1.72	0.45	0.00	0.00	0.00	3.00	12.28
Max	327.00	1.72	0.50	196.20	60.00	1.00	28.00	41.21
Mean	239.98	1.72	0.47	87.01	26.61	0.93	14.39	22.70
Mode	327.00	1.72	0.45	0.00	0.00	1.00	7.00	14.30
Median	237.10	1.72	0.45	89.93	27.50	1.00	7.00	20.01
StDev	58.07	0.00	0.02	58.10	17.76	0.26	10.32	9.16
CL (95%)	15.55	0.00	0.01	15.56	4.76	0.07	2.76	2.45

1.6 Pearson's Correlation Coefficient

Pearson's product-moment is the method of determining the relationship between input and output variables. The Pearson's correlation coefficient has been calculated for compressive strength of GGBS mixed concrete, as given in Table 6 in terms of Pearson's matrix.

Table 6 – Pearson's matrix of datasets of GGBS mixed concrete

Correlation (R)	Cement (Kg)	C/F ratio	W C ratio	GG BS (Kg)	GG BS (%)	SP (%)	Age (Days)	CS (Mpa)
Cement (Kg)	1.00	-	-	-	-	-	-	-
C/F ratio	0.45	1.00	-	-	-	-	-	-
WC ratio	0.58	0.32	1.00	-	-	-	-	-
GGBS(Kg)	1.00	0.45	0.58	1.00	-	-	-	-
GGBS (%)	1.00	0.45	0.58	1.00	1.00	-	-	-
SP (%)	0.65	0.70	0.27	0.65	0.65	1.00	-	-
Age (Days)	0.22	0.39	0.52	0.22	0.22	0.29	1.00	-
CS (Mpa)	0.37	0.33	0.40	0.37	0.37	0.21	0.93	1.00

The graphical presentation of the relationship between input parameters and compressive strength of GGBS mixed concrete is shown in Figure. 2

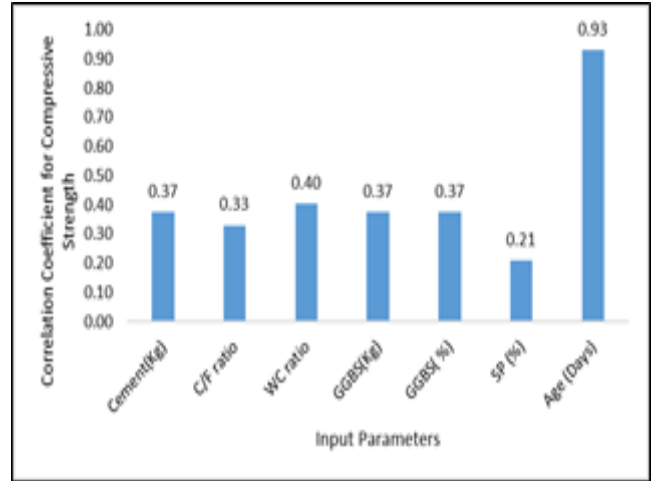


Figure 2. Relationship between input parameters and compressive strength

Figure 2 shows that the cement, C/F ratio, w/c ratio, GGBS, SP have a weak relationship with the compressive strength of concrete, but age (curing days) has a very strong correlation [11]. The correlation coefficient shows that the compressive strength of GGBS mixed concrete is influenced by curing days.

1.7 Training, Validation, and Testing Datasets

The regression analysis, support vector machine, decision tree, and artificial neural network models have been developed to predict the compressive strength. The datasets are divided into the following for developing AI models, as shown in Table 7.

Table 7 – Divisions of datasets used in this study

Approach	Training Data	Validation Data	Testing Data
MLR	43	-	13
SVM	43	-	13
DT	43	-	13
ANN	34	09	13

IV.RESULTS AND DISCUSSIONS

The results and performance of Multilinear Regression Analysis, Support Vector Machine, Decision Tree, and Artificial Neural Network have been discussed. The models have been developed to predict the compressive strength of GGBS mixed concrete. The performance of constructed AI models has been calculated in terms of MAE, RMSE, and R. The mathematical expression of MAE, RMSE, and R is –

$$MAE = \frac{1}{N} (\sum_{i=1}^N abs(T_i - P)_i) \tag{2}$$

$$RMSE = \sqrt{\frac{1}{N} \sum_{i=1}^N (T_i - P_i)^2} \tag{3}$$

$$R = \frac{\sum_{i=1}^N (T_i - \bar{T})(P_i - \bar{P})}{\sqrt{\sum_{i=1}^N (T_i - \bar{T})^2 \sum_{i=1}^N (P_i - \bar{P})^2}} \tag{4}$$

The best architecture model has been identified based on the performance of AI models.

The following four AI models have also been compared to identify the optimum performance AI model for predicting the compressive strength of GGBS mixed concrete specimen.

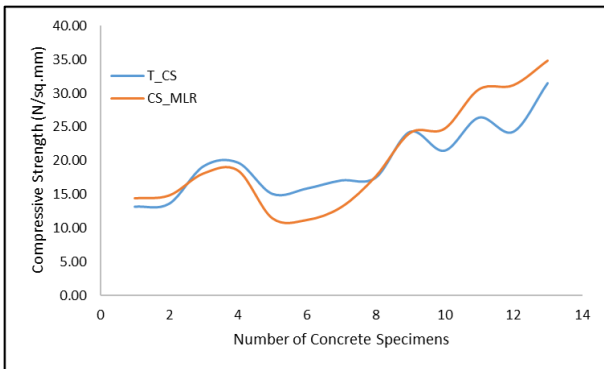
### 1.8 Multilinear Regression Analysis

The multilinear regression model (CS\_MLR) is used for predicting the compressive strength of GGBS mixed concrete. The training and testing performance of the CS\_MLR model is shown in Table 8.

**Table 8 – Performance of CS\_MLR Model for Cs of GGBS Mixed Concrete**

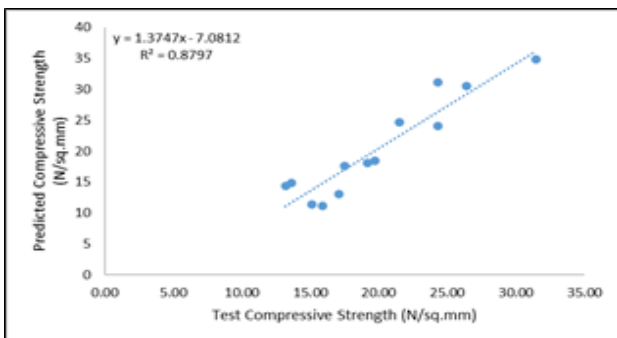
Training Performance			Testing Performance		
RMSE	R	MAE	RMSE	R	MAE
2.2053	0.9744	1.7274	3.3224	0.9379	2.6946

From Table 8, it has been observed that the CS\_MLR model has achieved a performance of 0.9379 in predicting the compressive strength of GGBS mixed concrete. The predicted and laboratory compressive strength of 13 GGBS mixed concrete specimens has been compared, as shown in Figure 3.



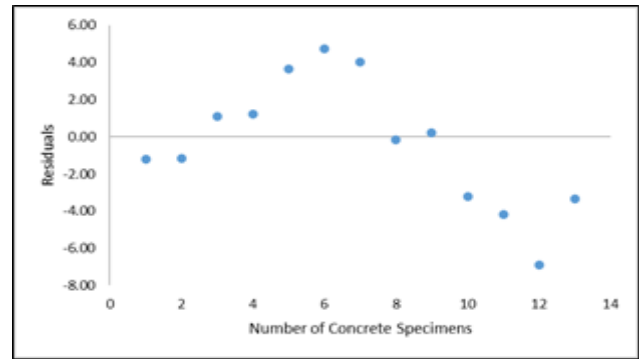
**Figure 3. Comparison of test and predicted CS using CS\_MLR model**

Figure 3 shows that the CS\_MLR has predicted compressive strength of GGBS mixed concrete approximately equal to laboratory results. Hence, the CS\_MLR model may be used for predicting the preliminary compressive strength of GGBS mixed concrete. The actual vs predicted plot is mapped to calculate the coefficient of determination. The coefficient of determination ( $R^2$ ) has been calculated for the predicted compressive strength of GGBS mixed concrete using the CS\_MLR model, as shown in Figure 4.



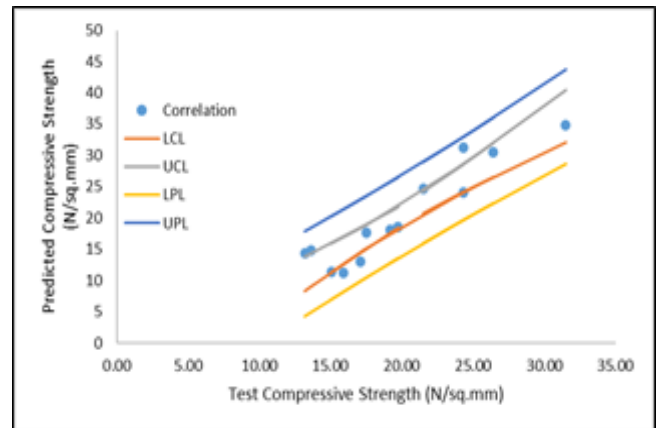
**Figure 4. R2 for the predicted CS using CS\_MLR model**

From Figure 4, it has been observed that the CS\_MLR model has predicted the compressive strength of GGBS mixed concrete with  $R^2 = 0.8797$ . The residuals in predicting the compressive strength of GGBS mixed concrete have been calculated, as shown in Figure 5.



**Figure 5. Residuals plot for predicted CS using CS\_MLR model**

From Figure 5, it has been observed that the CS\_MLR model has predicted the compressive strength of GGBS mixed concrete with the variation of  $\pm 8.0$ . The confidence and prediction interval of computed compressive strength of GGBS mixed concrete using the CS\_MLR model has been mapped, as shown in Figure 6.



**Figure 6. Confidence and prediction interval of computed CS using CS\_MLR model**

From Figure 6, it has been observed that the CS\_MLR model has predicted compressive strength of GGBS mixed concrete with  $\pm 5.65\%$  confidence and  $\pm 13.69\%$  prediction intervals.

### 1.9 Support Vector Machine

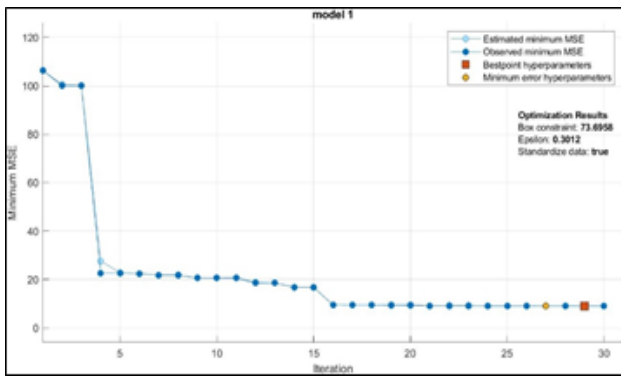
Four support vector machine models have been constructed using Linear, Gaussian, Quadratic, and Cubic kernel functions to compute the compressive strength of GGBS mixed concrete. The Linear, Gaussian, Quadratic, and Cubic kernel function-based SVM models are designated as LinK\_CS\_SVM, GaussK\_CS\_SVM, QuadK\_CS\_SVM, CubicK\_CS\_SVM, respectively. The training and testing performance of the SVM models of compressive strength of GGBS mixed concrete is shown in Table 9.

# Computation of Compressive Strength of GGBS Mixed Concrete using Machine Learning

**Table 9 – Performance of SVM Models for CS of GGBS Mixed Concrete**

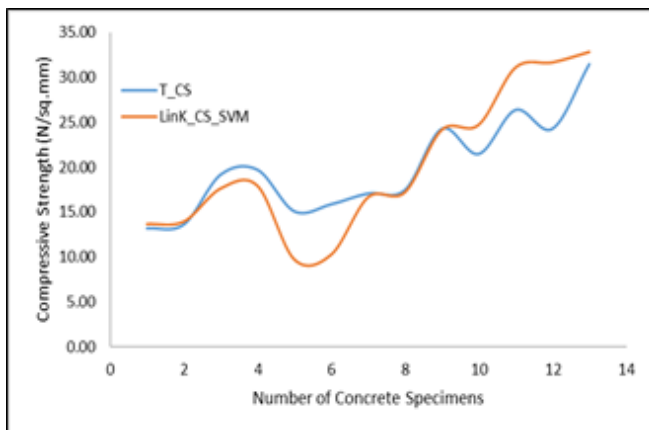
SVM Model Architecture	Training Performance			Testing Performance		
	RMS E	R	MAE	RMS E	R	MAE
LinK_CS_SVM	3.027 1	0.953 9	2.231 4	3.450 5	0.927 3	2.508 7
GaussK_CS_SV M	2.298 4	0.974 7	1.336 5	3.517 1	0.833 3	2.727 6
QuadK_CS_SV M	1.494 1	0.989 9	1.018 6	3.587 7	0.748 4	1.938 0
CubicK_CS_SV M	2.746 9	0.959 2	1.805 7	3.849 4	0.926 0	3.439 2

From Table 9, it has been observed that the LinK\_CS\_SVM model has achieved a maximum performance of 0.9273 in predicting the compressive strength of GGBS mixed concrete. The performance curve of the Link\_CS\_SVM model is shown in Figure 7.



**Figure 7. Performance of Link\_CS\_SVM model for predicting CS**

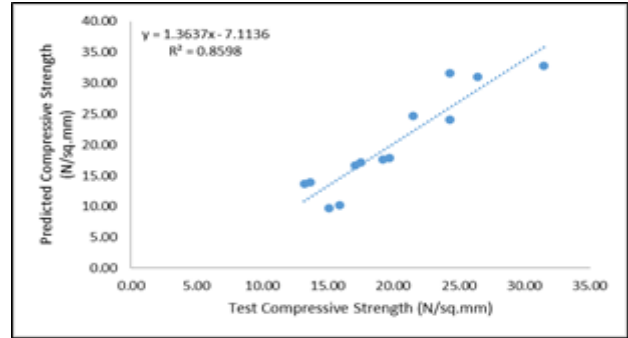
From Figure 7, it has been observed that the best prediction of compressive strength of GGBS mixed concrete has been achieved at the 29<sup>th</sup> iteration with RMSE = 3.4505, which is comparatively less than other SVM models of compressive strength of GGBS mixed concrete. The LinK\_CS\_SVM model has been used to predict the compressive strength, and predicted compressive strength has been compared with laboratory compressive strength, as shown in Figure 8.



**Figure 8. Comparison of test and predicted CS using LinK\_CS\_SVM model**

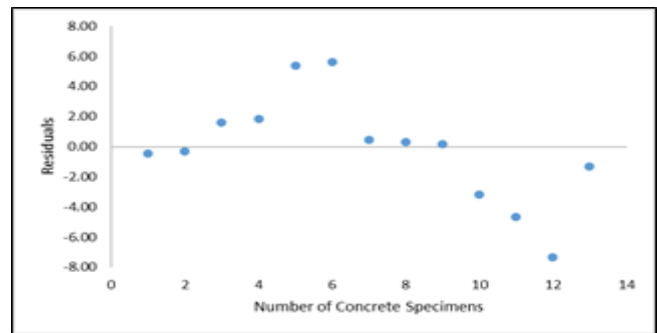
Figure 8 shows that the LinK\_CS\_SVM model has predicted the compressive strength of GGBS mixed concrete, which is nearly equal to laboratory results. Hence, the LinK\_CS\_SVM model may be used for predicting the

preliminary compressive strength of GGBS mixed concrete. The actual vs predicted plot is mapped to calculate the coefficient of determination. The  $R^2$  has been calculated for the predicted compressive strength of GGBS mixed concrete using LinK\_CS\_SVM, as shown in Figure 9.



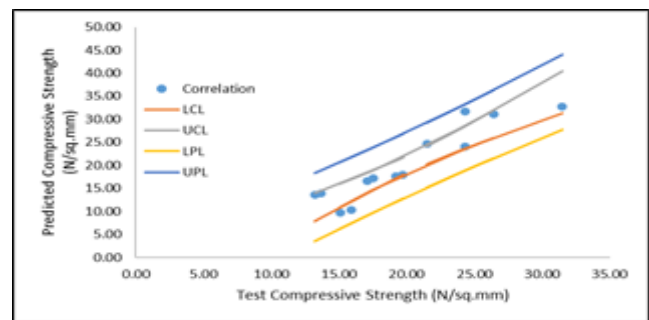
**Figure 9. R2 for the predicted CS using LinK\_CS\_SVM model**

From Figure 9, it has been observed that the LinK\_CS\_SVM models have predicted the compressive strength of GGBS mixed concrete with  $R^2 = 0.8598$ . The residuals in predicting the CS of GGBS mixed concrete have been calculated, as shown in Figure 10.



**Figure 10. Residuals plot for predicted CS using LinK\_CS\_SVM model**

From Figure 10, it has been observed that the LinK\_CS\_SVM model has predicted the compressive strength of GGBS mixed concrete with the variation of  $\pm 10.0$  in compressive strength. The confidence and prediction interval of computed compressive strength of GGBS mixed concrete using the LinK\_CS\_SVM model has been mapped, as shown in Figure 11.



**Figure 11. Confidence and prediction interval of computed CS using LinK\_CS\_SVM model**

From Figure 11, it has been observed that the LinK\_CS\_SVM model has predicted compressive strength of GGBS mixed concrete with  $\pm 6.12\%$  confidence and  $\pm 14.83\%$  prediction intervals.

1.9.1 Decision Tree

The decision tree (DT) model has been constructed using a twenty-leaf size to compute the compressive strength of GGBS mixed concrete. The decision tree model is designated as 20LF\_CS\_DT, where LF is leaf size selected automatically for the best prediction. The training and testing performance of the DT model of compressive strength of GGBS mixed concrete is shown in Table 10

Table 10 – Performance of DT Model for CS of GGBS Mixed Concrete

DT Model Architecture	Training Performance			Testing Performance		
	RMS E	R	MAE	RMS E	R	MAE
20LF_CS_DT	3.4227	0.938	2.110	1.8514	0.956	1.228

From Table 10, it has been observed that the 20LF\_CS\_DT model has achieved a performance of 0.9566 in predicting the compressive strength of GGBS mixed concrete. The performance curve of the 20LF\_CS\_DT model is shown in Figure 12.

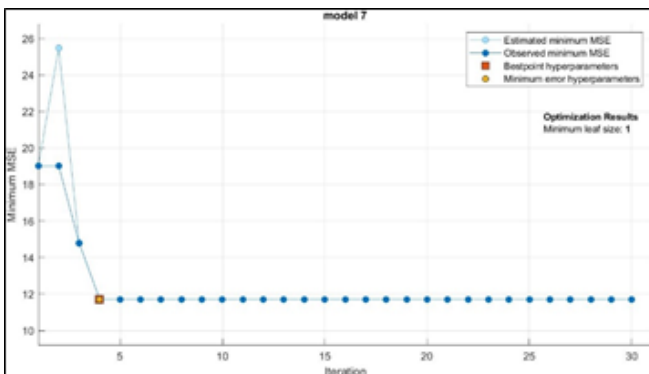


Figure 12. Performance of 20LF\_CS\_DT model for predicting CS of concrete

Figure 12 shows that the best prediction of compressive strength of GGBS mixed concrete has been achieved at the 4<sup>th</sup> iteration with RMSE = 0.9566. The 20LF\_CS\_DT model has been used to predict the compressive strength and predicted compressive strength has been compared with laboratory compressive strength, as shown in Figure 13.

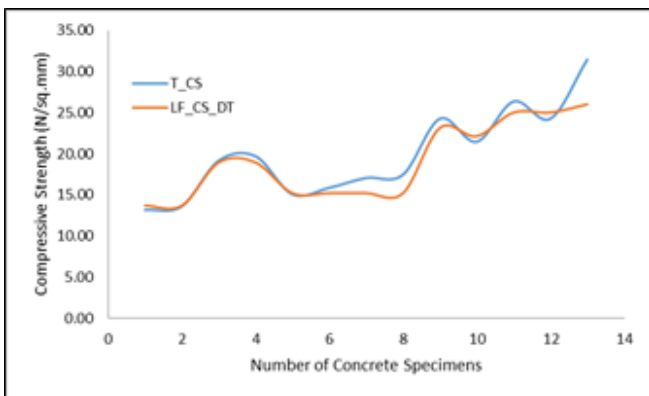


Fig- 13 Comparison of test and predicted CS using 20LF\_CS\_DT model

Figure 13 shows that the 20LF\_CS\_DT model has predicted the compressive strength of GGBS mixed concrete, which is equal to laboratory results. Hence, the 20LF\_CS\_DT model may be used for predicting the preliminary compressive strength of GGBS mixed concrete. The actual vs predicted plot is mapped to calculate the coefficient of determination. The coefficient of determination ( $R^2$ ) has been calculated for the predicted compressive strength of GGBS mixed concrete using 20LF\_CS\_DT, as shown in Figure 14.

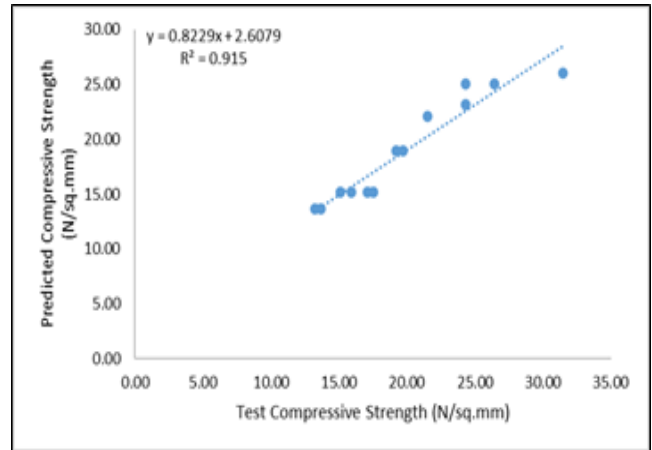


Figure 14 R2 for the predicted CS using 20LF\_CS\_DT model

Figure 14 shows that the 20LF\_CS\_DT models have predicted compressive strength of GGBS mixed concrete with  $R^2 = 0.9150$ . The residuals in predicting the compressive strength of GGBS mixed concrete have been calculated, as shown in Figure 15.

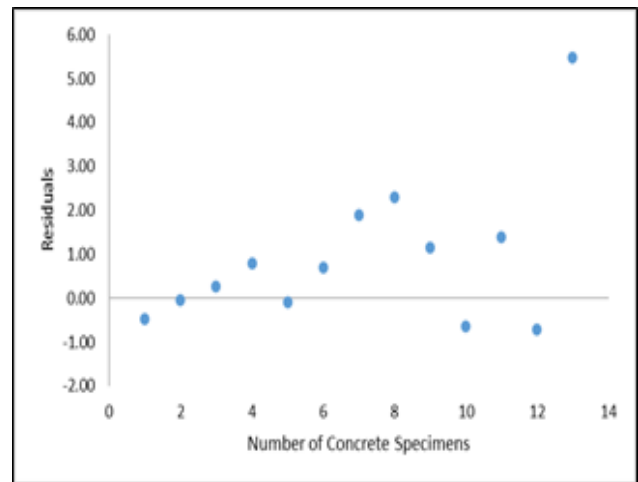


Figure 15. Residuals plot for predicted CS using 20LF\_CS\_DT model

From Figure 15, it has been observed that the 20LF\_CS\_DT model has predicted the compressive strength of GGBS mixed concrete with the variation of  $\pm 6.0$  in compressive strength. The confidence and prediction interval of computed compressive strength of GGBS mixed concrete using the 20LF\_CS\_DT model has been mapped, as shown in Figure 16.

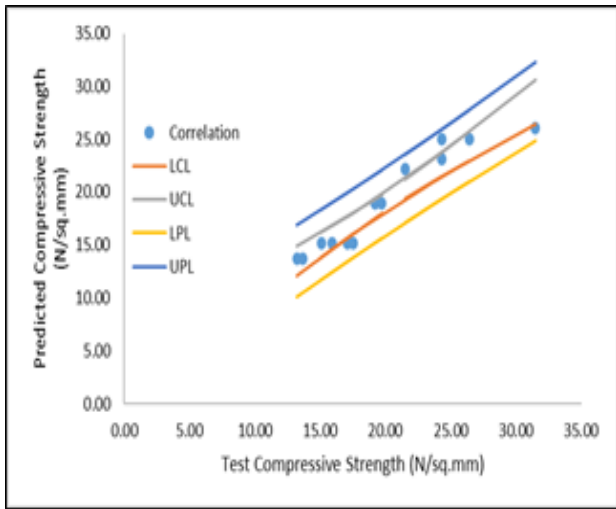


Figure 16. Confidence and prediction interval of computed CS using 20LF\_CS\_DT model

From Figure 16, it has been observed that the 20LF\_CS\_DT model has predicted compressive strength of GGBS mixed concrete with  $\pm 2.79\%$  confidence and  $\pm 6.76\%$  prediction intervals.

1.9.2 Artificial Neural Networks

The Artificial Neural Network models have been constructed using Levenberg-Marquardt (LM), Gradient Descent with Moment (GDM), Gradient Descent with Adaptive (GDA), BFGS Quasi-Newton (BFG), Scaled Conjugate Gradient (SCG), and Gradient Descent (GD) algorithms to predict the compressive strength of GGBS mixed concrete. The LM, BFG, SCG, GDM, GD, and GDA ANN models are designated as LM\_CS\_ANN, BFG\_CS\_ANN, SCG\_CS\_ANN, GDM\_CS\_ANN, GD\_CS\_ANN, and GDA\_CS\_ANN, respectively. The training and testing performance of the ANN models of compressive strength of GGBS mixed concrete is shown in Table 11.

Table 11 – Performance of ANN models for CS of GGBS Mixed Concrete

DT Model Architecture	Training Performance			Testing Performance		
	RMS E	R	MAE	RMS E	R	MAE
LM_CS_ANN	0.0906	0.9910	0.1775	3.6368	0.7400	3.0819
BFG_CS_ANN	0.0701	0.9818	0.0643	3.4792	0.9073	2.3166
SCG_CS_ANN	0.0663	0.9834	0.0775	4.7391	0.7458	3.3933
GDM_CS_ANN	0.0814	0.9780	0.0200	3.4055	0.9090	2.7923
GD_CS_ANN	0.1554	0.9119	0.1108	5.5053	0.4122	4.3426
GDA_CS_ANN	0.1101	0.9475	0.1631	7.6175	0.4985	5.1070

From Table 11, it has been observed that the GDM\_CS\_ANN model has achieved a maximum performance of 0.9566 in predicting the compressive strength of GGBS mixed concrete. The performance curve of the GDM\_CS\_ANN model is shown in Figure 17.

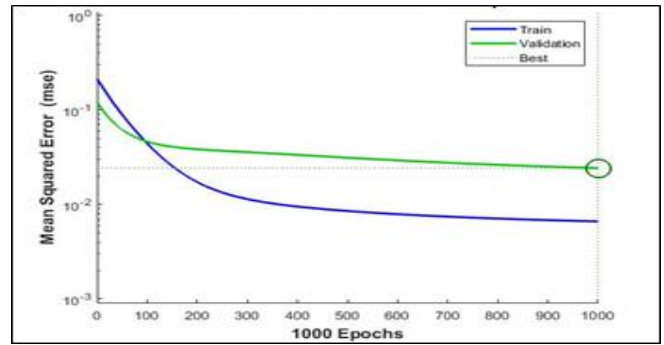


Figure 17. Performance of GDM\_CS\_ANN model for predicting CS of concrete

Figure 17 shows that the best prediction of compressive strength of GGBS mixed concrete has been achieved at the 1000<sup>th</sup> iteration with RMSE = 3.4055, which is comparatively less than other ANN models. The GDM\_CS\_ANN model has been used to predict the compressive strength and predicted compressive strength has been compared with laboratory compressive strength, as shown in Figure 18.

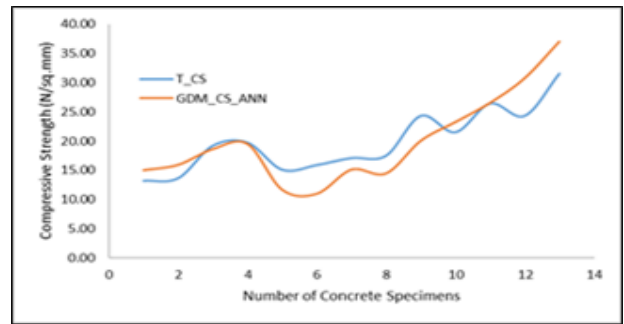


Figure 18. Comparison of test and predicted CS using GDM\_CS\_ANN model

Figure 18 shows that the GDM\_CS\_ANN model has predicted the compressive strength of GGBS mixed concrete, which is equal to laboratory results. Hence, the GDM\_CS\_ANN model may be used for predicting the preliminary compressive strength of GGBS mixed concrete. The actual vs predicted plot is mapped to calculate the coefficient of determination. The coefficient of determination ( $R^2$ ) has been calculated for the predicted compressive strength of GGBS mixed concrete using GDM\_CS\_ANN, as shown in Figure 19.

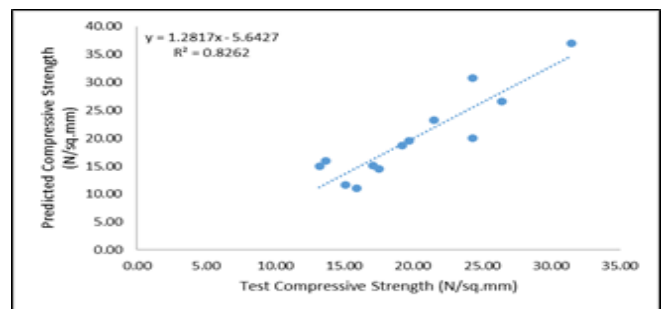


Figure 19. R2 for the predicted CS using GDM\_CS\_ANN model



From Figure 19, it has been observed that the GDM\_CS\_ANN model has predicted the compressive strength of GGBS mixed concrete with  $R^2 = 0.8262$ . The residuals in predicting the compressive strength of GGBS mixed concrete have been calculated, as shown in Figure 20.

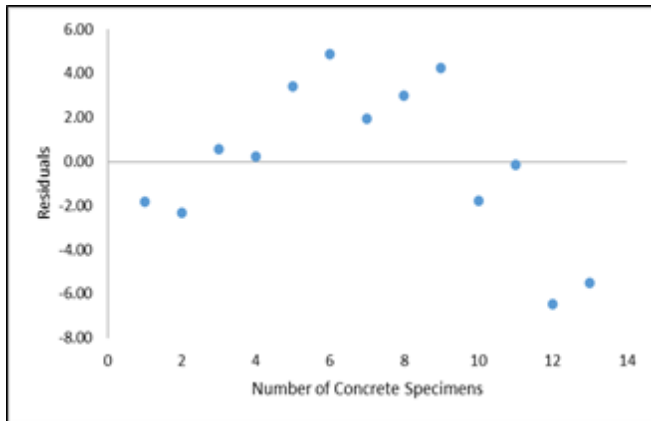


Figure 20. Residuals plot for predicted CS using GDM\_CS\_ANN model

From Figure 20, it has been observed that the GDM\_CS\_ANN model has predicted the compressive strength of GGBS mixed concrete with the variation of  $\pm 8.0$  in compressive strength. The confidence and prediction interval of computed compressive strength of GGBS mixed concrete using the GDM\_CS\_ANN model has been mapped, as shown in Figure 21.

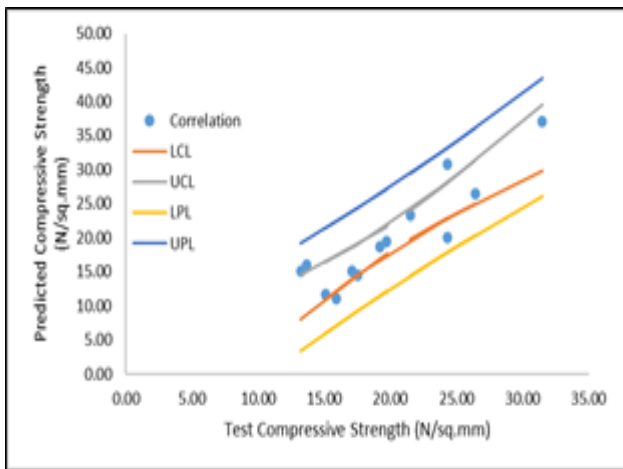


Figure 21. Confidence and prediction interval of computed CS using GDM\_CS\_ANN model

From Figure 21, it has been observed that the GDM\_CS\_ANN model has predicted compressive strength of GGBS mixed concrete with  $\pm 6.53\%$  confidence and  $\pm 15.84\%$  prediction intervals.

### 1.9.3 Optimum Performance Model

The CS\_MLR, LinK\_CS\_SVM, 20LF\_CS\_DT, and GDM\_CS\_ANN models have been identified as the best architectural AI models. The performance of the best architectural AI models has been compared to identify the optimum performance AI model for predicting the compressive strength of GGBS mixed concrete, as shown in Figure 22.

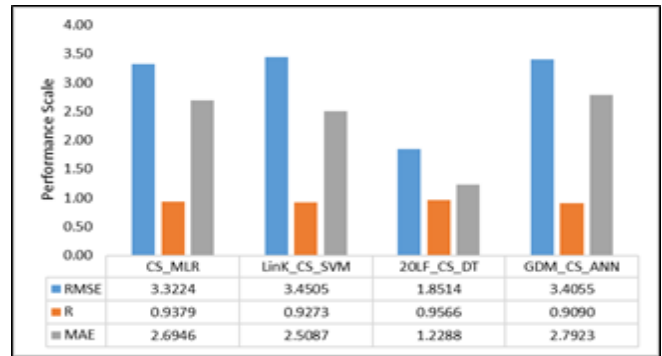


Figure 22. Performance comparison of the best architectural AI models for predicting CS

From Figure 22, it has been observed that the 20LF\_CS\_DT model of the decision tree AI approach has predicted compressive strength of GGBS mixed concrete with MAE = 1.2288, RMSE = 1.8514, and R = 0.9566, respectively. The coefficient of determination ( $R^2$ ) of 20LF\_CS\_DT shows a strong correlation with laboratory test results of compressive strength of GGBS mixed concrete[23]. The 20LF\_CS\_DT model outperformed the CS\_MLR, LinK\_CS\_SVM, and GDM\_CS\_ANN in predicting the compressive strength of GGBS mixed concrete. Hence, the 20LF\_CS\_DT model has been identified as the optimum performance model and can be used to predict the compressive strength of GGBS mixed concrete.

### V.COMPARISON WITH PUBLISHED MODELS

The 20LF\_CS\_DT model has been identified as the optimum performance model with a performance of 0.9566. The performance of the 20LF\_CS\_DT model has been compared with published models, as shown in Figure 23.

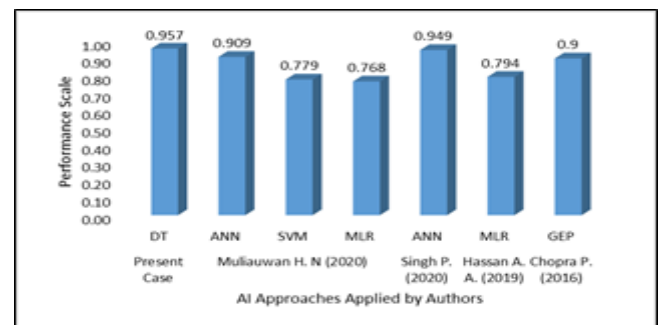


Figure 23. Comparison of performance of DT model with published models in the literature

Figure 23 shows that the 20LF\_CS\_DT model outperformed the published models in predicting the compressive strength of concrete. Hence, the 20LF\_CS\_DT model can be used to predict the compressive strength of waste materials or by-material mixed concrete.

### VI.CONCLUSIONS

The literature study shows that the AI approaches can predict the compressive strength of concrete. In the present study, the regression analysis, support vector machine, decision tree, and artificial neural network.

# Computation of Compressive Strength of GGBS Mixed Concrete using Machine Learning

AI approaches were used to predict GGBS mixed concrete's compressive strength. The following conclusions are mapped from the present study –

- The Pearson's correlation coefficient shows that the compressive strength of GGBS mixed concrete is influenced by days of curing.
- The performance of developed models shows that machine learning outperformed the statistical methods and deep learning with a performance of 0.9566.
- The statistical methods outperformed deep learning with a performance of 0.9379.
- The comparison of performance 20LF\_CS\_DT models outperformed the published models in the literature study.

From the study, it has been concluded that the decision tree with 20 leaf-size performs better and predicts the compressive strength of GGBS mixed concrete with high accuracy.

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